# Econ 311: Behavioral and Experimental Economics

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# Discrimination

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  - Example? Higher car insurance premium for teenagers

# Are Emily and Greg More Employable Than Lakisha and Jamal?

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- Want to examine racial discrimination in job hiring practices
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- Need an experimental design where race is truly randomly assigned
- Research design by Bertrand and Mullainathan (2004):
  - Create many composite resumes based on real ones
  - Some are high skill, some are low skill
  - Randomly put either white-sounding or African-American-sounding name on top of each resume
  - Send resumes to real hiring managers in response to 1300 real ads
  - Send 4 resumes (1 of each type) to each
  - Measure percentage of callbacks each resume gets

# Names Used Were Distinctly Black or White

TABLE A1—FIRST NAMES USED IN EXPERIMENT

| White female Name | L(W)/L(B) | Perception White | African-American female Name | L(B)/L(W) | Perception Black |
|---|---|---|---|---|---|
| Allison | ∞ | 0.926 | Aisha | 209 | 0.97 |
| Anne | ∞ | 0.962 | Ebony | ∞ | 0.9 |
| Carrie | ∞ | 0.923 | Keisha | 116 | 0.93 |
| Emily | ∞ | 0.925 | Kenya | ∞ | 0.967 |
| Jill | ∞ | 0.889 | Lakisha | ∞ | 0.967 |
| Laurie | ∞ | 0.963 | Latonya | ∞ | 1 |
| Kristen | ∞ | 0.963 | Latoya | ∞ | 1 |
| Meredith | ∞ | 0.926 | Tamika | 284 | 1 |
| Sarah | ∞ | 0.852 | Tanisha | ∞ | 1 |
| Fraction of all births: | | | Fraction of all births: | | |
| 3.8 percent | | | 7.1 percent | | |

| White male Name | L(W)/L(B) | Perception White | African-American male Name | L(B)/L(W) | Perception Black |
|---|---|---|---|---|---|
| Brad | ∞ | 1 | Darnell | ∞ | 0.967 |
| Brendan | ∞ | 0.667 | Hakim | | 0.933 |
| Geoffrey | ∞ | 0.731 | Jamal | 257 | 0.967 |
| Greg | ∞ | 1 | Jermaine | 90.5 | 1 |
| Brett | ∞ | 0.923 | Kareem | ∞ | 0.967 |
| Jay | ∞ | 0.926 | Leroy | 44.5 | 0.933 |
| Matthew | ∞ | 0.888 | Rasheed | ∞ | 0.931 |
| Neil | ∞ | 0.654 | Tremayne | ∞ | 0.897 |
| Todd | ∞ | 0.926 | Tyrone | 62.5 | 0.900 |
| Fraction of all births: | | | Fraction of all births: | | |
| 1.7 percent | | | 3.1 percent | | |

# Evidence for Discrimination

TABLE 1—MEAN CALLBACK RATES BY RACIAL SOUNDINGNESS OF NAMES

| | Percent callback for White names | Percent callback for African-American names | Ratio | Percent difference (*p*-value) |
|---|---|---|---|---|
| Sample: | | | | |
| All sent resumes | 9.65 | 6.45 | 1.50 | 3.20 |
| | [2,435] | [2,435] | | (0.0000) |
| Chicago | 8.06 | 5.40 | 1.49 | 2.66 |
| | [1,352] | [1,352] | | (0.0057) |
| Boston | 11.63 | 7.76 | 1.50 | 4.05 |
| | [1,083] | [1,083] | | (0.0023) |
| Females | 9.89 | 6.63 | 1.49 | 3.26 |
| | [1,860] | [1,886] | | (0.0003) |
| Females in administrative jobs | 10.46 | 6.55 | 1.60 | 3.91 |
| | [1,358] | [1,359] | | (0.0003) |
| Females in sales jobs | 8.37 | 6.83 | 1.22 | 1.54 |
| | [502] | [527] | | (0.3523) |
| Males | 8.87 | 5.83 | 1.52 | 3.04 |
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- Summary?

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- Summary? Resumes with white names 1.5 times more likely to get callback as identical resumes with black names

# Effect of Resume Characteristics

Table 5—Effect of Resume Characteristics on Likelihood of Callback

| Dependent Variable: Callback Dummy<br>Sample: | All resumes | White names | African-American names |
|---|---|---|---|
| Years of experience (*10) | 0.07 | 0.13 | 0.02 |
| | (0.03) | (0.04) | (0.03) |
| Years of experience$^2$ (*100) | −0.02 | −0.04 | −0.00 |
| | (0.01) | (0.01) | (0.01) |
| Volunteering? (Y = 1) | −0.01 | −0.01 | 0.01 |
| | (0.01) | (0.01) | (0.01) |
| Military experience? (Y = 1) | −0.00 | 0.02 | −0.01 |
| | (0.01) | (0.03) | (0.02) |
| E-mail? (Y = 1) | 0.02 | 0.03 | −0.00 |
| | (0.01) | (0.01) | (0.01) |
| Employment holes? (Y = 1) | 0.02 | 0.03 | 0.01 |
| | (0.01) | (0.02) | (0.01) |
| Work in school? (Y = 1) | 0.01 | 0.02 | −0.00 |
| | (0.01) | (0.01) | (0.01) |
| Honors? (Y = 1) | 0.05 | 0.06 | 0.03 |
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| Computer skills? (Y = 1) | −0.02 | −0.04 | −0.00 |
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| Special skills? (Y = 1) | 0.05 | 0.06 | 0.04 |
| | (0.01) | (0.02) | (0.01) |
| *Ho:* Resume characteristics effects are all zero (*p*-value) | 54.50<br>(0.0000) | 57.59<br>(0.0000) | 23.85<br>(0.0080) |
| Standard deviation of predicted callback | 0.047 | 0.062 | 0.037 |
| Sample size | 4,870 | 2,435 | 2,435 |

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- Summary? White names get much more credit for experience and education than black names

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    - Names that more common within a racial group are not more likely to get callback
  - Hiring managers actually prefer African-American candidates, and think others do too, so think they are harder to get
    - Discrimination among all types of jobs, including very desirable ones

# Gender

# Motivation

- So far we have focused in this class mostly on behavior of an entire population
- However, lots of evidence in economics of *individual differences* in race, gender, age, etc
- Gender is correlated with different risk preferences and social preferences, for example
- Gender especially easy to study because it is randomly assigned

# Risk Aversion Differences Between Men and Women

- Experiment by Eckel and Grossman (2002)
- Subjects choose one of five risky options
  - Choice 1 is lowest risk and lowest expected payoff
  - Choice 5 is highest risk and highest expected payoff
- Two framings
  - Loss frame: paid $6 for completing experiment
  - Gain frame: no fixed payment

Table 1
Gamble choices, expected payoffs, and risk in the two alternative framings

| | | | Payoff | | Expected payoff | | |
|---|---|---|---|---|---|---|---|
| Gamble choice | Event | Probability (%) | Loss framing ($) | No-Loss framing ($) | Loss framing ($) | No-Loss framing ($) | Risk |
| 1 | A | 50 | 10 | 16 | 10 | 16 | 0.00 |
| | B | 50 | 10 | 16 | | | |
| 2 | A | 50 | 18 | 24 | 12 | 18 | 4.24 |
| | B | 50 | 6 | 12 | | | |
| 3 | A | 50 | 26 | 32 | 14 | 20 | 8.48 |
| | B | 50 | 2 | 8 | | | |
| 4 | A | 50 | 34 | 40 | 16 | 22 | 12.73 |
| | B | 50 | −2 | 4 | | | |
| 5 | A | 50 | 42 | 48 | 18 | 24 | 16.97 |
| | B | 50 | −6 | 0 | | | |

The level of risk is represented as the S.D. of expected payoff.

# Men's Choices vs Women's Choices

Table 2
Frequency distributions of gamble choices in relation to the subject's sex and the framing treatment

| | All subjects | | Men | | Women | |
|---|---|---|---|---|---|---|
| Gamble choice | Loss framing | No-Loss framing | Loss framing | No-Loss framing | Loss framing | No-Loss framing |
| 1 | 7 | 3 | 2 | 0 | 5 | 3 |
| 2 | 25 | 10 | 11 | 6 | 14 | 4 |
| 3 | 48 | 17 | 15 | 10 | 33 | 7 |
| 4 | 32 | 9 | 18 | 6 | 14 | 3 |
| 5 | 36 | 13 | 26 | 10 | 10 | 3 |
| Total | 148 | 52 | 72 | 32 | 76 | 20 |
| Mean gamble choice (S.D.) | 3.44 (1.17) | 3.37 (1.22) | 3.76 (1.18) | 3.63 (1.13) | 3.14 (1.08) | 2.95 (1.28) |

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  - Some evidence for more risk-seeking in losses than in gains
- Question: can we say this is due entirely to biology?

# More Motivation

- We see employment differences between men and women in many dimensions
  - Wages
  - Choice of job
  - Choice to work at all
- What causes these differences?

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- We see employment differences between men and women in many dimensions
  - Wages
  - Choice of job
  - Choice to work at all
- What causes these differences?
  - One possibility: different risk preferences as we just saw
  - Another possibility: men and women interact differently with competitive environments

# Gender Differences in Competition

- Research design by Gneezy, Niederle, and Rustichini (2003)
  - Undergraduate engineering students
  - Groups of 6 students (3 men, 3 women)
  - Task: solving mazes of varying difficulty on the computer

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  1. Non-competitive
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  2. Competitive (tournament):
     - Person that solves most mazes gets 12 dollars for each maze solved
     - All others in group receive nothing
     - Winner anonymous

# Performance by Gender in Piece Rate

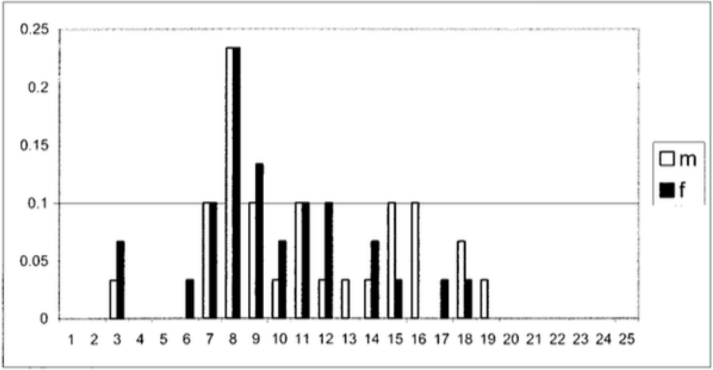


FIGURE I
Number of Mazes Solved under Piece Rate

# Performance by Gender in Tournament

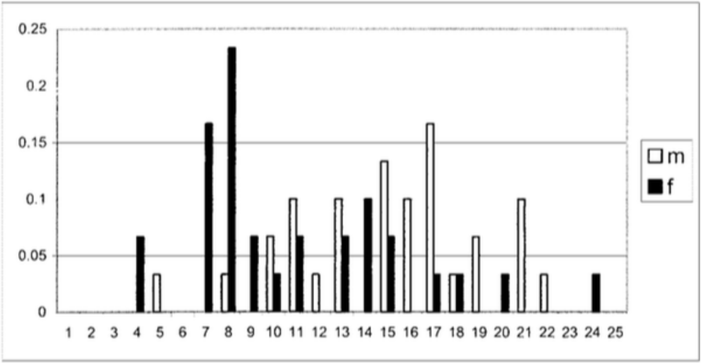


FIGURE II
Number of Mazes Solved under Tournament Condition

# Gender Gap

- In summary:
  - Small, statistically insignificant gender gap under piece rate (11.23 vs 9.73, $p = 0.202$)
  - Larger, statistically significant gender gap under tournament (15.00 vs 10.9, $p < .01$)
- What could be causing this performance gender gap in one setting but not the other?

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- What could be causing this performance gender gap in one setting but not the other?
  1. Women have maxed out their performance
  2. Women don't like competing
  3. Women don't like competing against men
  4. Women don't like uncertain payment

# Two Additional Treatments

1. Uncertain payment
   - One person chosen at random and paid 12 dollars for each maze solved correctly
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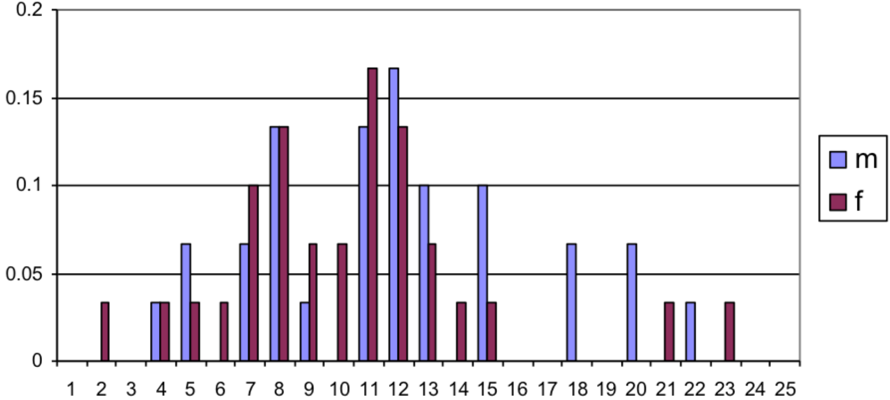
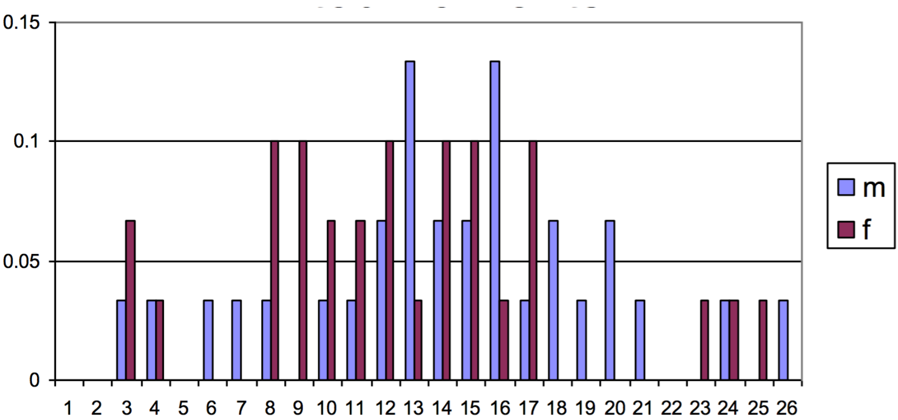
1. Uncertain payment
   - One person chosen at random and paid 12 dollars for each maze solved correctly
   - Score is private
2. Single-sex tournament:
   - Groups of all 6 men or all 6 women
   - Person that solves most mazes gets 12 dollars for each maze solved
   - All others in group receive nothing
   - Winner anonymous

# Uncertain Payment




Mean for males: 11.83, for females: 10.33. $p = 0.165$

# Single-Sex Tournaments




Men: 14.3, Women: 12.6, $p = 0.135$

# Summary of Results

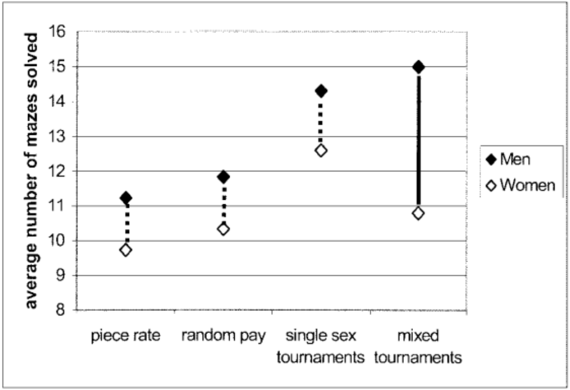



FIGURE III
Averages Performance of the 30 Men and 30 Women in Each of the Treatments

- Which theory is most consistent with data?

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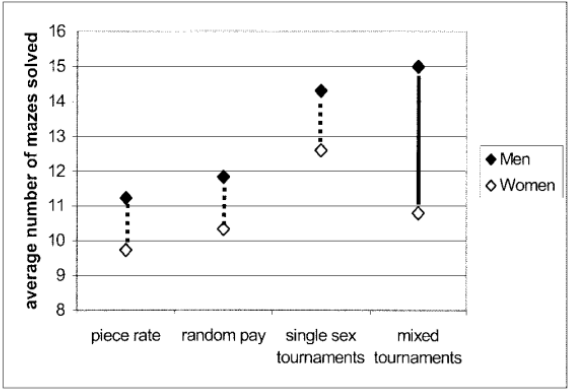


FIGURE III
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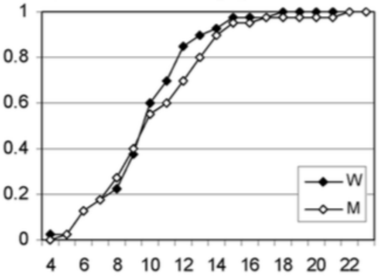
- Which theory is most consistent with data? Women don't like competing against men

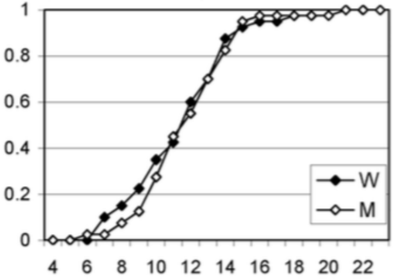
# Selection into Competitive Environments

- Main results from previous paper: significant gender gap seems to exist only when women are competing directly against men
- Natural question: are women aware of this preference, and do they consider it when choosing which environments to enter?
- Research design by Niederle and Vesterlund (2007):
  - Groups of 4 (2 men, 2 women)
  - Different task: add groups of 5 two-digit numbers
  - As before, two treatments: piece-rate (50 cents per correct answer) and tournament (2 dollars per correct answer for winner only)
  - Initially, subjects randomly assigned into a treatment

# Baseline Results: No Gender Gap in Performance




(A) Piece Rate




(B) Tournament

# Selection Into Tournament

- After 5 rounds of either piece-rate or tournament, subjects get to choose between the two for the next part of the study
- Based on performance we see in baseline, women and men are expected to do equally well in the tournament
  - Top 30% of both genders should choose tournament

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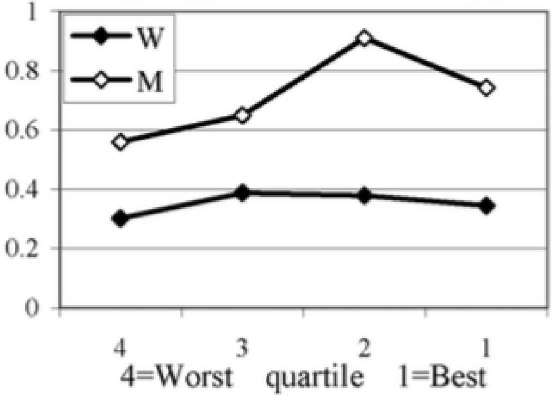
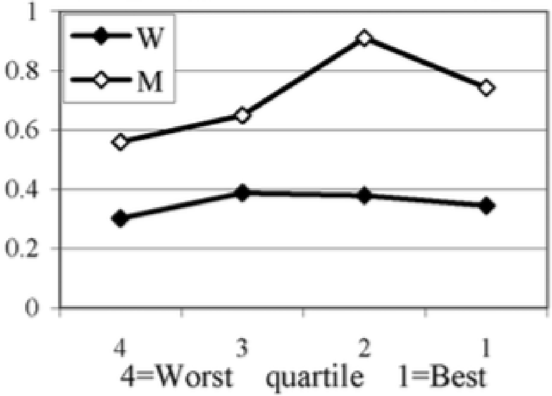
- What actually happens?
  - 35% of women choose tournament
  - 73% of men choose tournament

# Likelihood to Enter Tournament vs Ranking




- Summary?

# Likelihood to Enter Tournament vs Ranking




- Summary? Men's likelihood to enter tournament increases with rank in baseline group, but women's likelihood does not

# What Could Cause Difference?

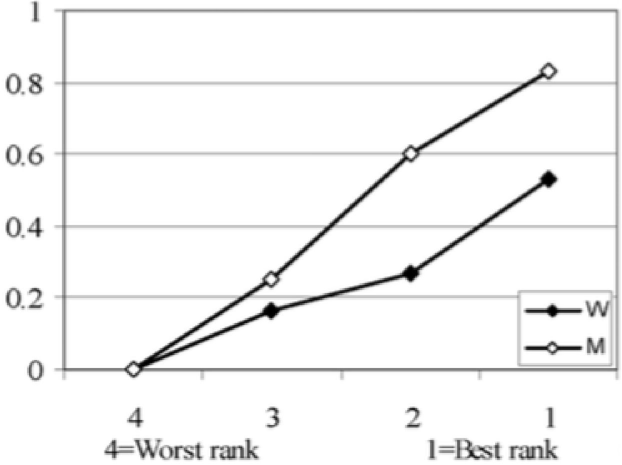
- What could be causing the difference in entrance rates?
- Perhaps women have lower confidence in their own rank
- So, authors ask subjects to report what they think their rank is within their group of 4
  - Paid 1 dollar if correct, nothing otherwise

# Men Supremely Over-Confident

DISTRIBUTION OF GUESSED TOURNAMENT RANK

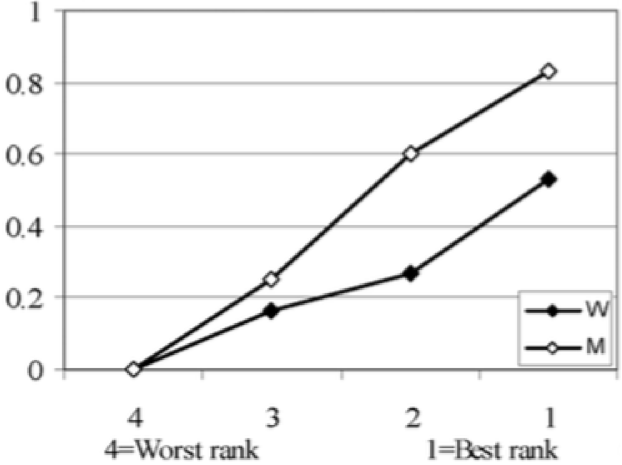
| | Men | | Women | |
|---|---|---|---|---|
| | Guessed rank | Incorrect guess | Guessed rank | Incorrect guess |
| 1: Best | 30 | 22 | 17 | 9 |
| 2 | 5 | 3 | 15 | 10 |
| 3 | 4 | 2 | 6 | 5 |
| 4: Worst | 1 | 1 | 2 | 1 |
| Total | 40 | 28 | 40 | 25 |

# Likelihood to Enter Tournament vs *Guessed* Ranking




- Summary?

# Likelihood to Enter Tournament vs *Guessed* Ranking




- Summary? Relative confidence does not fully explain gender gap